QCA 3.0: The "Ragin Revolution" Continues

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Redesigning Social Inquiry: Fuzzy Sets and Beyond, by **Charles C. Ragin.** Chicago, IL: University of Chicago Press, 2008. 225pp. $18.00 paper. ISBN: 9780226702759.

Since publishing *The Comparative Method* (*TCM*) more than two decades ago, Charles Ragin has become sociological methodology's George Wallace, Ross Perot, and Ralph Nader rolled into one. Defying the doctrines of the two major parties—quantitative and qualitative—Ragin has run an insurgent campaign dedicated to a principled alternative. In his latest book, *Redesigning Social Inquiry: Fuzzy Sets and Beyond* (*RSI*), Ragin continues his quest, claiming no less than to offer a "real alternative to conventional practices" that "is not a compromise between qualitative and quantitative" but rather "transcends many of their respective limitations" (p.6). Though some specifics have changed over twenty years, Ragin's overarching goal remains the same: to reshape the way sociologists think about and practice their research. As unrealistic as this goal may sound, *RSI* comes very close to making it seem possible.

At its most basic, *RSI* is motivated by the same critiques and offers the same solutions as 1987's *TCM* and 2000's *Fuzzy-Set Social Science* (*FSSS*). The quants' general linear model (GLM) is deemed problematic because it assumes away causal complexity, looking instead for linear, additive, and independent causal forces. The quals' case-based methods capture complexity but lack formal tools for the necessary task of generalizing across cases. Both limitations, Ragin argues, can be overcome by making explicit the set-theoretic logic of case-based research and by extending this logic to quantitative data via Boolean algebra. He maintains that the strengths of qualitative and quantitative analysis can be combined if we think of cases as *configurations of conditions* rather than as either *sui generis* or as the simple product of independent causal forces.[1] Despite this thematic consistency, potential readers should not make the mistake of thinking they have seen all this before—*RSI* contains a wealth of new techniques, procedures, and practical tips. For those new to QCA, *RSI* is undoubtedly the best place to begin as it provides the clearest and most concise introduction available.

One key difference between *RSI* and the previous books is its intended audience. *TCM* and *FSSS* were addressed primarily to comparative-historical or other case-focused researchers, with mainstream quantitative analysts a significant, but secondary focus. This time Ragin's arguments are intended to persuade quantoids—including survey analysts—to invest in QCA. As an opening olive branch, Ragin immediately acknowledges that the GLM is a "wonderful, well-articulated [research] template," while gently but firmly insisting that it is not "the *only* template" (p.1, emphasis in original). Rather than draw lines in the sand, he argues pragmatically (and I think correctly) that researchers who ignore QCA are missing out on a "powerful and productive alternative" (p.1) capable of detecting patterns that are invisible to standard techniques. Since his argument is that the proof of the pudding is in the eating, Ragin wants to be sure his readers have a spoon in hand—a "practical appendix" appears at the end of most chapters with step-by-step instructions for using fs/QCA, the free software downloadable from Ragin's website.

In line with the change in intended audience and the more practical focus, *RSI* is organized into four parts that explore "four oppositions" between QCA and the GLM. This organization is slightly misleading, since Ragin discusses all four oppositions throughout the book rather than confining them to their designated sections. This serves to make the book flow more smoothly, but it can be irritating to search in vain for something that "should be" in Part III but is actually in Part I.

The first opposition Ragin considers is between set-theory (QCA) and correlations (GLM) as ways of modeling connections between concepts. We all know that *r*XY ("the correlation between X and Y") is the same as *r*YX; the order of the variables doesn't matter because correlations are *symmetrical.* Subset relations, on the other hand, are *asymmetrical.* That is, the proportion of Xs that are also Ys need not be the same as the proportion of Ys that are also Xs. To illustrate the importance of this difference, consider two dichotomous variables—scoring above the 50th percentile (620+) on the quantitative GRE and being admitted to Berkeley Sociology's graduate program in 2009. As one might suspect (or contrary to popular opinion?), the (tetrachoric) correlation between these variables is rather high (.60)—scoring well and being admitted are indeed associated. But if we look at the relationship asymmetrically, we learn something much more interesting: only 14 percent of those who scored above the 50th percentile were admitted (versus 10 percent overall), but *97 percent* of those who were admitted scored above the 50th percentile. Decomposing associations, Ragin shows, allows us to search for patterns in the data consistent with hypotheses of causal necessity or sufficiency. Rather than hear about the strength of the correlation, a prospective grad student would likely find it more useful to hear that though scoring above the median on the GRE-Q is not *sufficient* for gaining admission to the program, doing so is very close to being *necessary.* Such relationships are relatively clear with two dichotomous variables, of course, but *RSI* offers procedures for extending this logic to multiple predictors and to non-dichotomous (fuzzy) sets. When Ragin reminds us that a matrix of symmetrical correlations is ultimately what's "under the hood" in everything from OLS to factor analysis to struc-

[1] Understanding this helps clarify the subtext of the book's title. Whereas King, Keohane, and Verba's *Designing Social Inquiry* extends the logic of quantitative analysis into the qualitative realm, Ragin's *Redesigning Social Inquiry* formalizes the logic of case-based analysis and extends it to the quantitative domain.

tural equation modeling, it does make one wonder how many interesting asymmetrical relationships are missed in even the most rigorous quantitative analyses.

Part II builds upon *FSSS*'s introduction of fuzzy sets into QCA and contrasts "measurement" with "calibration." Measured variables use arbitrary units like inches, dollars, and standard deviations. Calibrated fuzzy sets, on the other hand, reflect each case's degree of membership (from 0 to 1) in conceptual categories like "tall," "religious," or "developed." Set membership values are therefore *concept-relative* as well as *case-relative*. Calibration is the process of translating a variable into a set using a function derived from substantive knowledge. If we had a hypothesis about the "economically disadvantaged," for instance, the difference between $5,000 and $10,000 in annual income might matter a great deal for defining the set while the difference between $75,000 and $80,000 would not matter at all. Above a certain amount, income is no longer relevant *for membership in that particular set.* I have been amazed and perplexed over the past few years to find how controversial this idea really is. The main criticism is that calibrating "throws away variation," as if arbitrarily assuming constant effects on Y for every unit change in X (or, e.g., ln(X)) were somehow a natural virtue. In any case, *RSI*'s contribution beyond *FSSS* is to provide two new techniques for calibrating variables ("direct" and "indirect"), each of which relies on different combinations of user knowledge and mathematical interpolation. Both are easy to implement and will be especially handy for sensitivity analyses. Nevertheless, they are certain as the sunrise to be criticized by those who prefer the "see no evil" approach to functional form.

Part III moves into more advanced territory, contrasting the ways that the GLM and QCA handle causal inference with multiple possible causes. QCA's claim to fame is that it eschews the demolition derby of variation partialling in favor of searching for "causal recipes" whose individual conditions are jointly sufficient to produce an outcome with at least some degree of regularity. For fuzzy-set applications, *RSI* improves substantially on *FSSS* by adapting *TCM*'s truth table method for fuzzy data. Constructing a truth table means generating all possible 0/1 (or low/high) combinations of the predictor sets and using the data to evaluate the "subsetness" of each of them in the outcome set. Configuratons determined to be subsets of the outcome can then sometimes be combined and simplified using Boolean algebra. For instance, if the truth table showed that both "If A and B and C, then Y" and "If A and B and *not* C, then Y" were (probabilistically) true, this could be simplified to "If A and B, then Y." This is not just a matter of procedure, but a reflection of deeper assumptions. The GLM begins with a null hypothesis of causal simplicity but might be persuaded (if asked) to include some complexity with interaction terms; QCA, by contrast, begins with the null hypothesis of causal complexity and can be simplified only with positive evidence.

Assuming complexity may have the advantage of verisimilitude, but it also has some side effects. The first chapter of Part IV (co-authored with John Sonnett) deals with perhaps the most difficult of these—empty data spaces. Imagine we are trying to explain outcome Y using predictors A, B, and C. Imagine further that we find that "A and B and *not* C" is a subset of the outcome and that we have no empirical cases where A and B and C all occur together. Should we conclude that A and B are sufficient to produce Y *despite* the absence of C or *because* of its absence? Without additional information, it would be impossible to say. But what if previous research had consistently shown that C promotes Y? Could we use that side information to favor the first conclusion? Ragin and Sonnett explore such situations by distinguishing between "easy" and "difficult" counterfactuals. Easy counterfactuals permit simplifying a solution when we have a strong basis for inferring that the addition of a new condition to an otherwise sufficient combination of conditions should not decrease the likelihood of the outcome. (Difficult counterfactuals are those for which we simply don't know.) Skeptics should remember that empty data spaces are an issue for the GLM as well, but because it works upwards from simplicity this is rarely recognized. In the example above, for instance, the GLM would assume that the effects of A and B are constant across values of C; adding interaction terms would not help because the absence of cases in the relevant data space makes them impossible to test. The GLM, in other words, incorporates "difficult counterfactuals" by default. (Lest one think that this problem is restricted to small-N situations, I suggest median-splitting the variables from a recent model and collapsing them to see just how empty the data space really is.) This is an important issue and Ragin does us a service by forcing us to think about it. Furthermore, the straightforward implementation of this procedure in the software makes this a powerful tool.

The final chapter of the book provides something that *FSSS* sorely lacked—an extended comparison between QCA and the GLM using the same data. Ragin (and coauthor Peer Fiss) reexamine the *Bell Curve* data to investigate the relationship between poverty and cognitive ability. I won't ruin the surprise for those curious to see what they find, but the QCA results tell us something different than either the original or my colleagues' reanalysis in *Inequality by Design*. Beyond the specifics, this chapter is invaluable both because it walks the user through the types of decisions required at various stages of analysis and because it shows quantitative researchers that even survey data can be analyzed with QCA. Would-be users of QCA would do well to imitate this example, comparing their findings to GLM results where possible.

On the whole, *RSI* is a marvelous book—excellent in its own right as well as a major improvement over (and complete replacement for) *TCM* and *FSSS*. It is not, however, without its flaws. Foremost among them, to my mind, is Ragin's reluctance to address in more detail the *connections and affinities* between QCA and the GLM. It is true that contrasts can be more effective rhetorically (they "energize the base"), but by now I had hoped that Ragin would be equally interested in building bridges. How does crisp-set QCA compare to loglinear models? Why do fuzzy subset relations look like heteroskedacticity? Could truth tables be constructed with predicted probabilities? Discussions around issues like these could provide a segue between these research paradigms. Curious quantoids shouldn't feel required to renounce all claims to valid knowledge before checking out QCA. Second, it would have also been helpful if Ragin had discussed in more detail how these four oppositions are (and are not) detachable from the larger QCA framework. Might our research be better, for example, if we incorporated asymmetry into our thinking even if we still care about net effects? Can sufficiency be modeled without assuming causal complexity? While one of QCA's advantages is its coherence across these domains, social research as a whole would benefit enormously from thinking carefully about questions like these. Now that QCA is on a firm methodological footing of its own, I hope that the next steps involve creating connections where they are possible.

One final thing: I can imagine many readers asking themselves, "If QCA is as great as it sounds, why isn't it more widely used?" Sure, QCA appears fairly regularly in the discipline's top journals, but if it can *really* combine the strengths of qualitative and quantitative analysis and transcend their limitations, why is it still a niche method? Why hasn't it swept the field? There are many reasons. Beyond the fact that its complexity makes QCA more demanding to use correctly, Ragin has faced—as all third party candidates do—an uphill battle against institutional inertia. The norms of graduate training and our regular rituals of self-identification (e.g., quantoid, ethnographer) create subtle disincentives to investing in a "third way." (Plus, why spend 15 percent of your word count explaining QCA when typing "logistic regression" is so much more economical?) Such institutional explanations have value, of course, but I would argue that Ragin's difficulties have also been partly self-inflicted. His campaign has sometimes seemed designed to resonate much better with the discipline's qualitative minority, at least some of whom already had an axe to grind with the GLM. Compounding this is that some well-intentioned but misguided converts have given QCA a bad name by claiming things on its behalf that are simply impossible. No method, no matter how ingenious, can solve the problems of causal inference or causal complexity in a single stroke, yet I have reviewed several papers where authors make such claims. My sense is that the naïve enthusiasms of some have scared off the curiosity of many, including most of those in the GLM-ing majority. This is hardly a recipe for institutional success.

But this time may be different. The current methodological détente and the rage for mixed methods is a disciplinary ecology that might allow QCA to thrive. Much depends on the reaction of quantitative researchers. If they can keep an open mind, *Redesigning Social Inquiry* might be the right book at the right time to persuade them to try QCA for themselves. As a fellow quantoid, I am confident that they won't be disappointed if they do.